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RESEARCH ARTICLE

The Effects of Express Lane Eligibility on Medicaid and CHIP Enrollment among Children

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Objective. To estimate the impact of Express Lane Eligible (ELE) implementation on Medicaid/CHIP enrollment in eight states.

Data Sources/Study Setting. 2007 to 2011 data from the Statistical Enrollment Data System (SEDS) on Medicaid/CHIP enrollment.

Study Design. We estimate difference-in-difference equations, with quarter and state fixed effects. The key independent variable is an indicator for whether the state had ELE in place in the given quarter, allowing the experience of statistically matched non-ELE states to serve as a formal counterfactual against which to assess the changes in the eight ELE states. The model also controls for time-varying economic and policy factors within each state.

Data Collection/Extraction Methods. We obtained SEDS enrollment data from CMS.

Principal Findings. Across model specifications, the ELE effects on Medicaid enrollment among children were consistently positive, ranging between 4.0 and 7.3 percent, with most estimates statistically significant at the 5 percent level. We also find that ELE increased combined Medicaid/CHIP enrollment.

Conclusions. Our results imply that ELE has been an effective way for states to increase enrollment and retention among children eligible for Medicaid/CHIP. These results also imply that ELE-like policies could improve take-up of subsidized coverage under the ACA.

Key Words. Evaluation design and research, health economics, program evaluation, state health policies, Express Lane Eligiblity, Medicaid

Nearly 4.0 million uninsured children are eligible for Medicaid or the Children's Health Insurance Program (CHIP) (Kenney, Anderson, and Lynch 2013). Prior research attributes nonparticipation in Medicaid and CHIP, through low take-up or poor retention, to a host of factors, including lack of information about program eligibility, administrative hassle, and policy design complexities (Currie 2006; Remler and Glied 2003). To address some of these barriers, the Children's Health Insurance Program Reauthorization Act of 2009 (CHIPRA) gave states the option to implement Express Lane Eligibility (ELE). ELE allows a state's Medicaid and/or CHIP program to rely on another agency's eligibility findings to qualify children for public health insurance coverage, despite their different methods of assessing income or otherwise determining eligibility (Hoag et al. 2012).[1]

ELE has the potential to efficiently increase Medicaid and CHIP enrollment by allowing state Medicaid and CHIP agencies to use data already acquired by other agencies to determine program eligibility. States can choose from among 13 approved public agencies with which to partner or can obtain and use information directly from state income tax returns. ELE is regarded as a promising strategy for increasing enrollment in public coverage because so many low-income uninsured children's families participate in other government programs or file taxes: Kenney et al. (2010) estimate that ELE could reach 15 percent (724,000) of eligible uninsured children who qualify for health coverage based on their participation in the Supplemental Nutrition Assistance Program (SNAP), while Dorn et al. (2009) estimate that 89 percent (4.9 million) of uninsured children who qualified for Medicaid or CHIP in 2004 lived in families that filed federal income tax returns.

This is the first analysis of which we are aware that quantifies the impact of ELE policies adopted by the first eight states with such policies under CHIPRA.[2] This study, which was done as part of a congressionally mandated evaluation of ELE, uses 2007 to 2011 Medicaid and CHIP quarterly enrollment data available for all states through the Statistical Enrollment Data System (SEDS) to assess changes in Medicaid and CHIP enrollment in states after ELE implementation, using changes occurring over the same period in other states as a counterfactual. This impact analysis relies on multivariate models to account for possible confounding policy, demographic and economic changes, and time-invariant differences between ELE states and non-ELE comparison states that may be driving Medicaid or CHIP enrollment changes and might otherwise be incorrectly attributed to ELE adoption or mask the effects of ELE. For example, five of the eight ELE states increased Medicaid or CHIP thresholds for children between 2007 and 2011, whereas only 13 non-ELE states increased thresholds. Similarly, eight states, including three ELE states,

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added continuous eligibility—where any enrolled child maintains coverage for 12 months from the time of enrollment—to their Medicaid or CHIP programs between 2007 and 2011.

Background on ELE Programs

As of June 2011, eight states had received Center for Medicare and Medicaid Services (CMS) approval of ELE state plan amendments. In contrast with other enrollment and retention policies that have common structural features, ELE programs vary across states: they can apply to initial eligibility determination or redetermination, they can apply to Medicaid alone, CHIP alone, or both programs, they can apply to any Medicaid/CHIP eligibility factor other than citizenship (e.g., income, residency, etc), and they can utilize different levels of technology and automation. Below we briefly describe each program; Table 1 summarizes the programs, with a focus on the implementation assumptions used for the empirical analysis.

Six ELE states have programs that partner with other government agencies that provide benefits to low-income children. Alabama uses data from Temporary Assistance for Needy Families (TANF) and the Supplemental Nutritional Assistance Program (SNAP) to establish income eligibility for Medicaid renewals (effective October 2009) and initial applications (April 2010). Effective on January 1, 2011, Georgia's ELE program partnered with the Special Supplemental Nutrition Program for Women, Infants and Children (WIC), using that program's findings to establish income, residency, and identity for initial applications to Medicaid and CHIP. Implemented in June 2010, Iowa uses SNAP findings to establish all Medicaid eligibility factors except citizenship and immigration status. Iowa also has an ELE program that makes automatic referrals from Medicaid to CHIP. Louisiana uses ELE to qualify children for Medicaid based on SNAP determinations of income, state residence, Social Security Number, and identity. This initiative began in February 2010 with eligibility retroactive to December 2009. Oregon uses SNAP (effective statewide in September 2010) and National School Lunch Program (NSLP) findings (effective November 2011 as a pilot program) to establish income-eligibility and state residence for Medicaid and CHIP initial applications. In April 2011, South Carolina began redetermining Medicaid eligibility based on SNAP and TANF findings about income and assets.

Table 1: States with Approved State Plan Amendments for ELE as of January 2012

State	*Health Program*	*Express Lane Program(s)*	*Actual ELE Implementation Date*	*Date as Modeled (Fiscal Quarter, Year)*	*No. of Post-ELE Quarters*
Alabama I	Medicaid	SNAP; TANF	10/1/2009	Q1 2010	8
Alabama II	Medicaid	SNAP; TANF	4/1/2010	Q3 2010	6
Georgia	Medicaid and CHIP	WIC	1/1/2011	Q2 2011	3
Iowa	Medicaid and CHIP	SNAP; Medicaid*	6/1/2010 (SNAP); 7/1/2010 (Medicaid)	Q4 2010	5
Louisiana I	Medicaid	SNAP	2/10 for applications; 10/10 for renewals	Q2 2010	7
Louisiana II	Medicaid	SNAP	12/9 for applications; 10/10 renewals	Q1 2010	8
Oregon	Medicaid and CHIP	SNAP; NSLP (pilot)	8/1/2010 for SNAP[†]; 11/11 for NSLP	Q4 2010	5
South Carolina	Medicaid	SNAP; TANF	4/1/2011	Q3 2011	2
New Jersey	Medicaid and CHIP	State income tax; NSLP (pilot)	5/1/2009	Q3 2009	10
Maryland I	Medicaid	State income tax	5/1/2008 (tax-based outreach)	Q1 2009[§]	12
Maryland II	Medicaid	State income tax	4/1/2010 (tax-based ELE)	Q3 2010	6

Note. For states with two rows, the first row corresponds to the implementation date used for the main analysis, and the second row corresponds to the sensitivity analysis date. Federal fiscal year quarters are as follows: first quarter, October 1 through December 31; second quarter, January 1 through March 31; third quarter, April 1 through June 30; and fourth quarter, July 1 to September 30.

*This program uses one-way Medicaid-to-CHIP ELE referrals. There are no CHIP-to-Medicaid ELE referrals. ELE is used for redeterminations that result in a child being transferred from Medicaid to CHIP.

[†]The SNAP initiative was effective statewide in September 2010 but approved by CMS in August.

[‡]New Jersey's ELE program is authorized for applications and renewals, but officials claim ELE has been used only for initial applications at this point (Hoag et al. 2012).

[§]Maryland's tax-based outreach program was implemented in May 2008, but applications were not sent out until September.

CHIP, Children's Health Insurance Program; ELE, Express Lane Eligibility; NSLP, National School Lunch Program; SNAP, Supplemental Nutrition Assistance Program; TANF, Temporary Assistance for Needy Families; WIC, Special Supplemental Nutrition Program for Women, Infants and Children.

Source: Analysis of CHIP and Medicaid State Plan Amendments, Centers for Medicare & Medicaid Services.

New Jersey and Maryland have ELE programs that work through income tax returns to ask parents to identify their uninsured dependents. New Jersey uses income tax data to establish identity and income. Parents whose tax returns flagged their children as uninsured are sent streamlined ELE application forms, which they must complete and return to obtain an eligibility determination. For initial Medicaid applications, Maryland uses state income tax data to establish state residence. CMS officially recognized Maryland's process as an ELE program effective April 2010, after the state modified its procedures to use tax filings to establish state residency. However, since September 2008, the Maryland Department of Health and Mental Hygiene has partnered with the Office of the Comptroller to conduct outreach to tax filers whose children are potentially eligible for Medicaid (Hoag et al. 2012). We assume, for evaluation purposes, that Maryland's ELE program was implemented when the state began tax-based outreach during the first fiscal quarter of 2009 (which began in October 2008), but we also estimate models assuming the official CMS approval date of April 1, 2010.

DATA

SEDS Data

SEDS is a web-based system maintained by CMS since 2000 that collects new and total Medicaid and CHIP enrollment data from states on a quick-turnaround quarterly basis. States must submit quarterly enrollment data within 30 days after the end of the fiscal quarter and aggregate annual data within 30 days after the end of the fourth quarter. We use the SEDS because no other data were available that span the period of analysis. For example, other administrative data sources, such as the Medicaid Analytic eXtract (MAX) and the Medicaid Statistical Information System (MSIS), a state eligibility system capable of providing more detailed data (e.g., basic enrollee characteristics, utilization, and payments), have a multi-year lag period.[3]

This study uses the 2007 to 2011 quarterly SEDS data on total enrollment (the unduplicated number of children ever enrolled during the fiscal quarter). Throughout the analysis, we define Medicaid enrollment to include both traditional Medicaid and CHIP-funded Medicaid expansions. We define total Medicaid/CHIP enrollment to include enrollment in traditional Medicaid, CHIP-funded Medicaid expansions, and separate CHIP programs. Quarterly data prior to 2007 are excluded due to reporting errors and high item nonresponse rates.

We undertook a number of steps to develop a reliable SEDS dataset. We addressed quality issues in the quarterly data by imputing missing values and repairing reporting errors on a case-by-case basis, using annual SEDS data and point-in-time monthly enrollment counts from state Medicaid enrollment reports as quality checks (Snyder et al. 2012). Quarterly SEDS data points were also cross-validated against MSIS estimates, when available. We also addressed missing data and reporting errors by imputing SEDS data for some quarters and dropping some states where the data did not meet a sufficient quality threshold for inclusion. Our imputation strategy, which uses interpolation in most instances, is consistent with procedures that prior researchers developed while working with the annual SEDS data (Ellwood, Merrill, and Conroy 2003). We made imputations on less than 5 percent of state-quarter observations and the final analysis file, with the imputations, was approved by CMS-SEDS analysts. Based on results from outlier tests and confirmation from CMS, two non-ELE states, Maine and Montana, were excluded from this analysis due to concerns about data reliability.[4]

Finally, it is important to note that one limitation of the SEDS is that it only includes aggregate enrollment data and does not provide more detailed information—individual characteristics, claims, etc.—that researchers are typically interested in. This analysis can only estimate the impact of ELE on total enrollment, but it cannot decipher whether ELE is picking up children who are systematically different from other children enrolled in Medicaid.[5]

Additional Data Sources

The multivariate analysis attempts to account for changes in economic and demographic conditions that might otherwise bias estimates of the ELE effect. The main period of analysis is dominated by a recession that began in 2007, when unemployment rose and more people were living in families without a full-time worker. To control for the link between the unemployment rate and the overall loss of employer-sponsored coverage (Holahan and Garrett 2009; Cawley, Moriya, and Simon 2011), we use quarterly state unemployment rate data from the Bureau of Labor Statistics. We also use annual data from the U.S. Census Bureau to control for changes in the state child population over time.

From 2007 to 2011, several states expanded Medicaid/CHIP eligibility to higher income children and introduced changes to their enrollment and renewal processes, aimed at reducing the number of children who are eligible for Medicaid and CHIP but remain uninsured (Heberlein et al. 2012; Wachino and Weiss 2009). We control for non-ELE Medicaid and CHIP state policy changes using information on the implementation dates of various policies (Cohen-Ross, Cox, and Marks 2007; Cohen-Ross, Horn, and Marks 2008; Cohen-Ross and Marks 2009; Cohen-Ross et al. 2009; Heberlein et al. 2011, 2012). We include the following Medicaid and CHIP policy covariates: eligibility thresholds for parents and children, joint application for Medicaid and CHIP, presumptive eligibility, administrative verification of income,[6] no in-person interview, elimination of asset test, and continuous eligibility. We did not include the elimination of an asset test in Medicaid because no state in our sample made changes to this policy during the period of analysis. Changes in Medicaid/CHIP policies specifically among ELE and non-ELE states are described in detail in the online appendix.

We use the 2011 Current Population Survey to simulate adult and child eligibility for each state consistent with the method developed by Cutler and Gruber (1996). This method applies each state's eligibility thresholds to a standardized national sample of parents and children, as opposed to a particular state's own population, removing time-variant factors and differences in the income distribution across states. This variable captures the generosity of each state's eligibility criteria and is not confounded by varying conditions across or within states over time.

METHODS

Research Design

We estimate two-way fixed effect difference-in-difference equations with balanced panels as our main models for this analysis, where the eight ELE states constitute the treatment group (with the intervention occurring at different points in time for each state) and matched non-ELE states with similar pre-2009 enrollment trends comprise the comparison group. We estimate separate regression models for total Medicaid/CHIP enrollment and for Medicaid enrollment only[7]:

$$\begin{aligned}\log(\text{McaidCHIP})_{i,t} = \alpha + \beta_1\text{ELE}_{i,t} + \beta_2\text{OTHERPOLICY}_{i,t} \\ + \beta_3\text{COVARIATES}_{i,t} + \gamma_i + \delta_t + \epsilon_{i,t}\end{aligned} \quad (1)$$

$$\begin{aligned}\log(\text{Medicaid})_{i,t} = \alpha + \beta_1\text{ELE}_{i,t} + \beta_2\text{OTHERPOLICY}_{i,t} \\ + \beta_3\text{COVARIATES}_{i,t} + \gamma_i + \delta_t + \epsilon_{i,t}\end{aligned} \quad (2)$$

Where α is the intercept term, i is an index for state, t is an index for unique quarter, γ_i is a set of state dummy variables, δ_t is a set of quarter-specific dummy variables, and $\varepsilon_{i,t}$ is a random error term. The dependent variable, Log (Mcaid CHIP)$_{i,t}$, is the log of the number of children ever enrolled in Medicaid or CHIP in state i during quarter t, and Log(Medicaid)$_{i,t}$ corresponds to the number of children ever enrolled in Medicaid. We report robust standard errors clustered at the state level to correct for possible heteroskedasticity and autocorrelation (Bertrand, Duflo, and Mullainathan 2004). Unless otherwise noted, only findings that are significant at the .10 level (two-tailed test) are discussed.

The key independent variable of interest is ELE$_{i,t}$, which is set to one when the observation is an ELE state and the quarter either contains the month when ELE was implemented or is after ELE implementation. This variable measures the effects of ELE on Medicaid/CHIP or on Medicaid-only enrollment, depending on the model. With a log transformed dependent variable, the estimated ELE coefficient reflects the percent change in total enrollment associated with ELE implementation.

The state fixed effects, γ_i, help control for time-invariant differences across states that could be correlated with the ELE variable, such as inherent differences between ELE-states and non-ELE states, for example, potential differences in reporting accuracy of the SEDS data. The quarter fixed effects, δ_t, control for factors common to all states that vary from quarter to quarter.

OTHERPOLICY contains state-policy variables, and COVARIATES is a set of other state-level controls that vary over time and that could influence Medicaid/CHIP enrollment. In the combined Medicaid/CHIP model (1), OTHERPOLICY includes the simulated Medicaid/CHIP eligibility thresholds for children, the simulated Medicaid eligibility thresholds for parents, and dummy indicators for the presence of administrative simplification programs in Medicaid and CHIP. In the Medicaid-only model (2), we do not include the CHIP-specific policy variables. In the main specification, COVARIATES includes the state-quarter specific unemployment rate and year-state child population estimates that are log transformed.

Choosing Comparison States

Difference-in-difference models only provide consistent estimates of the treatment effect, if in the absence of the policy intervention, the time path in the outcome is the same for both the treatment and comparison states (Meyer 1995). For example, if Medicaid enrollment is trending upwards (downwards) to a larger extent within the comparison group relative to the ELE states in the pre-ELE period, the difference-in-difference model will understate (overstate) the benefits of ELE implementation. Given the widespread variation in Medicaid/CHIP participation, enrollment, and policies across states, we anticipate that some non-ELE states will have similar trends in enrollment compared to ELE states, while others will have dissimilar trends.

Using a statistical matching procedure to choose a control group, consistent with the method used by Lien and Evans (2005) to estimate the impacts of cigarette tax hikes, we select comparison states that had similar pre-ELE trends in Medicaid and Medicaid/CHIP enrollment as the ELE states. Since the first ELE program was implemented in 2009, we focus on trends in the 2007 and 2008 quarters prior to adoption of ELE. To select the comparison states, we estimate models similar to (1) and (2) that include a time trend and time trend interacted with an "ELE state" indicator. We include one non-ELE state at a time and test if the average trend among ELE states differs from the trend for that non-ELE state. If we reject the hypothesis at the 5 percent level that the coefficient associated with the interaction term equals zero, we exclude the non-ELE state from the sample, thus increasing the likelihood of choosing comparison states that possess a similar trend in Medicaid or Medicaid/CHIP enrollment as the average treatment state prior to ELE implementation.

The final Medicaid model includes 33 comparison states and the final Medicaid/CHIP model includes 25 comparison states. In the Medicaid model, we exclude Arizona, Colorado, Illinois, Nevada, New Mexico, Virginia, Washington, and Wyoming from the comparison group. In the combined Medicaid/CHIP model, we exclude Arizona, California, Connecticut, Florida, Illinois, Indiana, Kentucky, Missouri, Nevada, New Mexico, North Dakota, Ohio, Tennessee, Texas, Virginia, and Washington. Maine and Montana are excluded from both models.

Characterizing ELE Effects

Any attempt to characterize the effects of ELE must be seen in the context of a policy that can vary widely in both its implementation and target population. This underscores the importance of assessing the effects of ELE within individual states as a way to best understand the ELE models that might be most effective. To do so, we re-estimate the main model excluding one ELE state at a time to determine if the overall effect is primarily driven by the ELE experience in single state or if the ELE effect seems to vary across states. This analysis also assesses whether ELE works instantaneously or gradually by estimating a model that interacts the main ELE variable with a "number of quarters since ELE adoption" variable (set to zero for pre-ELE implementation and for non-ELE states).

We also estimate several models to assess the effects of ELE for groups of states based on the type of ELE program. We create different ELE policy variables—"ELE through SNAP," "ELE through tax returns," "ELE with simplified applications," "ELE with automatic processing," etc.—to explore whether there appeared to be a differential effect based on the type of ELE program implemented. These analyses are intrinsically exploratory given the many dimensions on which ELE programs can and do vary across states and given the variable size of the post-ELE experience across states adopting the different models.

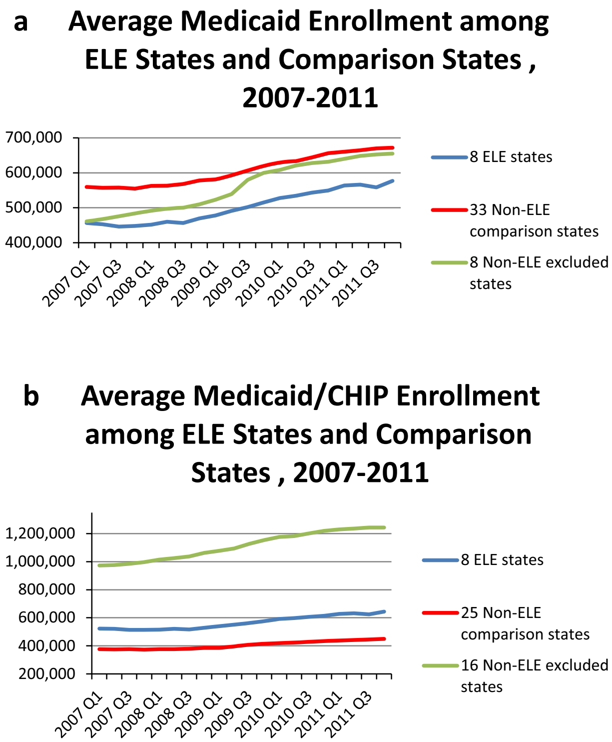
Sensitivity Tests

We conduct a series of robustness checks to explore the consistency of the ELE parameter estimates. These robustness checks include re-estimating the main model with alternative specifications of the control variables to determine the source of the ELE effects and alternative specifications with respect to how the comparison group is defined, such as excluding non-ELE states in a systematic manner to determine if specific control states are driving the main results. See appendix for additional discussion of these sensitivity tests.

RESULTS

Figure 1a and b show the trends in average Medicaid/CHIP and Medicaid enrollment among the eight ELE states, the chosen comparison states, and the excluded non-ELE states. Both figures show that ELE and comparison states had comparable enrollment trends before 2009, prior to the implementation of ELE in any state; the average 2007–2008 quarterly growth rate was approximately 0.4 percent among the ELE and comparison states in the Medicaid model (Figure 1a) and 0.3 percent in the Medicaid/CHIP model (Figure 1b). However, the descriptive data highlight quarter-to-quarter changes in enrollment only among ELE and non-ELE states and do not provide an estimate of the causal effect of ELE, as the precise post-period varies among each ELE state. By taking into account the scattered implementation of ELE policies and controlling for prevailing trends, fixed differences across states, and time-varying effects, the multivariate analysis

Figure 1: (a) Average Medicaid Enrollment among ELE States and Comparison States, 2007–2011. (b) Average Medicaid/CHIP Enrollment Among ELE States and Comparison States, 2007–2011



Note. (1) Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. (2) ELE states include Alabama, Georgia, Iowa, Louisiana, Maryland, New Jersey, Oregon, and South Carolina. Maine and Montana are excluded from all samples. (3) Non-ELE excluded states have an enrollment trend that significantly differs (at the 5 percent level) from the average trend among ELE states during the 2007–2008 period. *Source*: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

provides a more accurate characterization of the overall effects of ELE on Medicaid/CHIP enrollment.

Findings from the main multivariate difference-in-difference models show statistically significant evidence of a positive effect of ELE on enrollment (Table 2). On average, the main model, which uses the sets of comparison states described above, indicates that ELE implementation increased combined Medicaid/CHIP enrollment by 4.2 percent (statistically significant at

Table 2: Results from Main Multivariate Regression Models: Estimated Effects on Medicaid/CHIP and Medicaid Enrollment among Children, 2007–2011 Quarterly SEDS Data

	Dependent Variable (Log Transformed)	
	Total Medicaid/CHIP Enrollment	*Medicaid Enrollment Only*
Express lane eligibility	0.0420* (0.024)	0.0562** (0.026)
Unemployment rate	0.0067 (0.006)	0.0055 (0.006)
Log (child population)	0.8550** (0.381)	1.209*** (0.414)
Separate CHIP	0.0120 (0.023)	−0.0104 (0.017)
Simulated eligibility threshold for children	0.0003 (0.001)	0.0005 (0.001)
Simulated eligibility threshold for parents	−0.0024 (0.002)	−0.0037 (0.002)
Joint application	−0.0331 (0.027)	−0.0279 (0.027)
Presumptive eligibility-Medicaid	0.0589 (0.042)	0.0192 (0.026)
Admin. verification of income-Medicaid	0.0222 (0.050)	0.0635*** (0.023)
No in-person interviews-Medicaid	0.0390 (0.061)	0.0254 (0.042)
Continuous eligibility-Medicaid	0.0443 (0.049)	0.0375 (0.028)
Presumptive eligibility-CHIP	−0.0153 (0.044)	N/A
Admin. verification of income-CHIP	−0.0108 (0.053)	N/A
No in-person interviews-CHIP	0.0281 (0.052)	N/A
No asset test-CHIP	0.0273 (0.061)	N/A
Continuous eligibility-CHIP	0.0120 (0.051)	N/A
Constant	1.005 (5.295)	−3.995 (5.776)
R-squared	0.99	0.99
Sample size	660	820

Note. Robust standard errors clustered at the state level are in parentheses. All models include state and quarter fixed effects (coefficients not shown). Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.
$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.
Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

the 10 percent level) and Medicaid enrollment by 5.6 percent (statistically significant at the 5 percent level), holding all other observed policy and economic changes constant.

The estimated ELE impacts on Medicaid enrollment are robust with respect to the different specifications we tested (Table 3). Across a series of alternative models that address different potential sources of specification error and bias, we consistently find a positive estimated ELE effect, supporting the findings from the main model. In all of the alternative models, the ELE

Table 3: Estimated ELE Effects on Medicaid/CHIP and Medicaid Enrollment among Children: Alternative Specifications, 2007–2011 Quarterly SEDS Data

	Dependent Variable (Log Transformed)	
	Medicaid/CHIP Enrollment	*Medicaid Enrollment Only*
Main regression model	0.0420* (0.024)	0.0562** (0.026)
Alternative specification of control variables		
(1) State and quarter fixed effects only (unadjusted model)	0.0349 (0.028)	0.0406 (0.025)
(2) Unadjusted model + policy variables	0.0471* (0.024)	0.0587** (0.026)
(3) Unadjusted model + unemp rate and child population	0.0346 (0.028)	0.0401 (0.025)
(4) Policy index instead of dummy variables	0.0478* (0.0280)	0.0518** (0.025)
Alternative specification of comparsion states		
(5) Include all 41 non-ELE states as comparison states	0.0335 (0.022)	0.0422 (0.026)
(6) 10% significance threshold for dropping comparison state	0.0360 (0.022)	0.0595** (0.026)
(7) 1% significance threshold for dropping comparison state	0.0377 (0.024)	0.0565** (0.025)
(8) Excluding states based on joint test	0.0244 (0.026)	0.0551* (0.029)
(9) Excluding outlier comparison states	0.0425** (0.020)	0.0726*** (0.023)
(10) Excluding top 5 and bottom 5 comparison states in terms of ELE effect	0.0364* (0.020)	0.0552** (0.024)
(11) Excluding top 10 and bottom 10 comparison states in terms of ELE effect	0.0277 (0.018)	0.0506* (0.025)
Alternative specification of ELE implementation dates		
(12) Alternative implementation date: Alabama	0.0438* (0.024)	0.0580** (0.026)
(13) Alternative implementation date: Maryland	0.0328 (0.021)	0.0495** (0.024)
(14) Alternative implementation date: Louisiana	0.0417* (0.010)	0.0545** (0.007)

Note. Robust standard errors clustered at the state level are in parentheses. Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter.

*$p < .1$, **$p < .05$, ***$p < .01$.

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

coefficient remains positive with a central tendency close to what we find in the main model; we find that the magnitude associated with the ELE variable in the total Medicaid/CHIP alternative models range from 2.4 to 4.8 percent and in the Medicaid-only alternative models range from 4.0 to 7.3 percent. For all of the other models where the results are not shown, we find that the ELE effect is also close to what we find in the main model.

While remaining consistently positive and statistically significant in the majority of cases, we do find that the precision of the estimated ELE effect varies across the model specifications. For instance, the estimated ELE coefficient in the basic unadjusted difference-in-difference model without time-varying covariates is still similar in magnitude to the main fully adjusted model result, but it is not statistically significant at conventional levels ($p = .11$ in the Medicaid model and .20 in the Medicaid/CHIP model). We also find that the ELE effect is slightly smaller in magnitude and not statistically significant at conventional levels ($p = .12$ in the Medicaid model and .14 in the Medicaid/CHIP model) when we use all 41 non-ELE states as the comparison group, as opposed to using states with similar pre-ELE enrollment trends. However, the estimates of the ELE effect from this model could be biased downward because they include comparison states with quarterly enrollment levels trending upwards relative to ELE states during the pre-implementation time period. These results are further discussed in the appendix.

Findings on Other Variables

According to the results in the main models, the log transformation of the child population has a positive and statistically significant effect on enrollment, as we'd expect (Table 2). These results imply that a 1 percent increase in a state's child population would yield a .86 percent increase in quarterly Medicaid/CHIP enrollment and a 1.21 percent increase in Medicaid enrollment on average, holding all else constant. The coefficient on the unemployment variable is 0.007 in the Medicaid/CHIP enrollment model and 0.005 in the Medicaid only model, but it is not statistically significant at conventional levels.

The remaining variables control for observed state-level changes in Medicaid/CHIP policy during the period of analysis. Holding all else constant, we find that administrative verification of income increases Medicaid enrollment by approximately 6.4 percent, a result consistent across the alternative specification models as well. None of the other policy variables are statistically significant at conventional levels in the main model and the estimated effects vary in magnitude and statistical significance depending on the model specification. However, across all alternative specification models, we find that the estimated effects of continuous eligibility, which range from 3.7 to 5.5 percent, and of presumptive eligibility, which range from 0.7 to 3.8 percent, have a central tendency consistent with what is found in the main model (3.8 and 1.9 percent for continuous eligibility and presumptive eligibility, respectively), although the estimates are not statistically significant at conventional levels in the majority of the alternative specifications estimated in Table 3.

Characterizing the ELE Effects

The results in Table 4 suggest that the ELE effect on Medicaid/CHIP and Medicaid enrollment varies across states. When we re-estimate each of the main models excluding one ELE state at a time, we find that the coefficient on the ELE variable is smaller in magnitude (compared to the main effect) when Iowa, Maryland, New Jersey, and Oregon are excluded, suggesting that the ELE effect may have been stronger in these four states. The ELE effect is no longer statistically significant at conventional levels in the combined Medicaid/CHIP model when these four states are individually removed from the Medicaid/CHIP model, whereas in the Medicaid model, only the exclusion of Oregon reduces the statistical significance associated with the ELE

Table 4: Estimated ELE Effects on Medicaid/CHIP and Medicaid Enrollment among Children: Different Subsets of ELE States, 2007–2011 Quarterly SEDS Data

	Dependent Variable (Log Transformed)	
	Total Medicaid/CHIP Enrollment	*Medicaid Enrollment Only*
Main regression model	0.0420* (0.024)	0.0562** (0.026)
Models excluding individual states		
Alabama	0.0509* (0.028)	0.0625** (0.030)
Georgia	0.0527** (0.024)	0.0642** (0.027)
Iowa	0.0295 (0.024)	0.0480* (0.028)
Louisiana	0.0554** (0.026)	0.0739*** (0.024)
Maryland	0.0325 (0.024)	0.0515* (0.026)
New Jersey	0.0382 (0.026)	0.0514* (0.027)
Oregon	0.0390 (0.024)	0.0344 (0.022)
South Carolina	0.0494* (0.026)	0.0636** (0.026)

Note. Robust standard errors clustered at the state level are in parentheses. All models include state and quarter fixed effects (coefficients not shown). All other right-hand side variables are the same as those in the Table 2 main results. Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter. The Medicaid/CHIP models include 660 and the Medicaid model includes 820 state-quarter observations.
$*p < .1$, $**p < .05$, $***p < .01$.
Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

coefficient below conventional levels (p = .12). Altogether, this suggests that no single state's experience is driving the average effect in the Medicaid model and that there is no apparent pattern with respect to the type of ELE strategy adopted.

The results in Table 5 suggest that ELE implementation may have had a sustained impact on Medicaid enrollment over the period of analysis. As indicated above, we explored this by including a continuous variable that measures the number of quarters since ELE was implemented in the state, along with an interaction term with the ELE dummy variable. We find that the interaction is positive and statistically significant at the 10 percent level in the Medicaid enrollment model only. This result hints that the ELE effect on enrollment could be stronger the longer states have had ELE in place. However, given the limited number of post-ELE implementation quarters, the sensitivity of this result across model specifications, and the discontinuous nature of ELE implementation in some states, we will provide more confident estimates of the pattern of ELE effects over time in a follow-up analysis that adds an additional six quarters of data.

We also find that grouping states by type of ELE program yields inconsistent results across model specifications (results not shown). While it would have been desirable to estimate the relative impact of various approaches to ELE, the small number of states in our sample, the unique features of each

Table 5: Estimated ELE Effect for Regressions That Model the ELE Effect over Time: 2007–2011 Quarterly SEDS Data

	Dependent Variable (Log Transformed)	
	Total Medicaid/CHIP Enrollment	*Medicaid Enrollment Only*
Main regression model	0.0420* (0.024)	0.0562** (0.026)
Number of quarters since ELE implementation		
ELE	0.0279 (0.024)	0.0374 (0.024)
ELE × Number of quarters since ELE implementation	0.00401 (0.003)	0.00509* (0.003)

Robust standard errors clustered at the state-level are in parentheses. All models include state and quarter fixed effects (coefficients not shown). All other right hand side variables are the same as those in the Table 2 main results. Total enrollment includes children who were ever enrolled in Medicaid or CHIP during the fiscal quarter. Medicaid enrollment only includes children who were ever enrolled in Title XIX or TItle XXI Medicaid during the fiscal quarter. The Medicaid/CHIP models include 660 and the Medicaid model includes 820 state-quarter observations.

$*p < .1$, $**p < .05$.

Source: CMS Statistical Enrollment Data System (SEDS) as of March 30, 2012, verified and provided by CMS.

state's ELE process, and limitations of available data make it challenging to obtain meaningful results. In future years, as additional states implement ELE and more enrollment data become available, multivariate analyses like this study may yield valuable insights about the relative effectiveness of different types of ELE processes.

DISCUSSION

Our impact analysis finds significant evidence that ELE implementation under CHIPRA increased Medicaid enrollment. Across a series of model specifications, estimated impacts of ELE were consistently positive, ranging between 4.0 and 7.3 percent, with most estimates statistically significant at the 5 percent level. Overall, these estimates had a central tendency of about 5.5 percent. The analyses also find evidence that ELE increased Medicaid/CHIP enrollment. Across a series of models, estimated impacts were consistently positive, although not always statistically significant at conventional levels, with a central tendency of about 4.2 percent. Our findings also suggest that ELE might have an extended effect over time rather than a one-time increase, although this finding should be viewed with caution given the short post-ELE period available at the time of this analysis. Even though most ELE policies were implemented quickly, unlike other eligibility and enrollment simplification strategies that might diffuse slowly, our results suggest that the positive effect of ELE on enrollment had not phased out over time, at least during the post-ELE window we were able to observe.

Our results suggest that ELE has similar enrollment impacts compared with other administrative simplification policies. For example, while not a focus on this analysis, we find that administrative verification (i.e., self-declaration) of income, a policy similar to ELE, is associated with a 6 percent gain in total Medicaid enrollment. This result is consistent with the findings from Kronebusch and Elbel (2004), who find that administrative verification of income increased CHIP enrollment by 3.5 in 2000.

The less robust evidence of an effect of ELE on combined Medicaid/CHIP enrollment is not surprising given how modestly ELE has been implemented for CHIP. At the time of this analysis, only four states implemented ELE through CHIP, one of which (Iowa) had an ELE-like policy in effect prior to the period of analysis. We would also expect the effects from Oregon and Georgia's ELE programs would be heavily weighted toward Medicaid, because each state's Express Lane agency, WIC and SNAP, respectively, has income eligibility levels that encompass the Medicaid threshold but which are below the CHIP threshold. In other words, these findings do not mean that ELE policies cannot affect CHIP enrollment, but rather that the existing ELE programs are more targeted toward Medicaid as opposed to CHIP enrollment.

While our results suggest that ELE can have a positive effect on Medicaid enrollment, it is uncertain how this finding might generalize to a particular state or state program. We find that ELE had an above average effect on enrollment in Iowa and Oregon, where ELE primarily functioned through SNAP, and in Maryland and New Jersey, where ELE functioned through the tax system as an outreach tool. However, the experience for any individual state could vary widely due to differences in policy design, implementation, or its target population.

As we have indicated, unobservable factors might bias our estimated ELE effects. Specifically, unless accounted for in our models, factors that are correlated with the timing of ELE adoption that also affect enrollment might bias our estimates of ELE effects. For example, some states might have upgraded their information technology systems or implemented targeted outreach programs, subsequently increasing enrollment, at the same time they carried out ELE. Should such factors concurrently increase enrollment in ELE states and not be accounted for in our set of policy covariates, it could introduce upward bias in our estimates. Alternatively, should non-ELE states be pursuing such unmeasured initiatives, it could bias our impact estimates downward. While acknowledging the potential risk of bias, we have conducted a series of robustness checks that raise confidence in our findings. The estimated effects of ELE vary only slightly across sensitivity tests and are not driven by the inclusion of a single variable (or set of variables) or by the inclusion or exclusion of a single ELE state or comparison state. Despite our attempts to control for potentially confounding policy changes, it is impossible to draw definitive conclusions about the precise magnitude of ELE impacts on enrollment, given the heterogeneous nature of ELE programs and the limited information we have about enrollment changes following ELE implementation in many states that adopted ELE. While this analysis is certainly suggestive that ELE policies have positive enrollment effects, caution is warranted in interpreting these estimates as causal.

Fiscal cliff negotiations extended ELE through September 2014, highlighting the importance of continuing to track the impacts of ELE on child enrollment in current and future ELE states, and assess whether the effects are sustained over time. Most of the ELE policies were approved in 2010 or later and unlike other eligibility and enrollment simplification strategies that may diffuse slowly, ELE policies were quickly implemented and the effect could phase out over time, depending on the details of state policy. Moving toward the implementation of the coverage provisions of the Affordable Care Act (ACA), our results show that states can apply ELE-like principles (e.g., streamlined applications, elimination of duplicative paper documentation, sharing of data across agencies) to make optimal use of existing databases to enroll and retain individuals in Medicaid/CHIP or subsidized Exchange coverage. Specifically, ELE principles could help policy makers achieve high take-up in Medicaid among adults, whose participation lags far behind that of kids and who are the target of the ACA Medicaid expansion (Kenney et al. 2012). ELE could also have beneficial effects beyond enrollment gains, as a recent report suggests that ELE could save time and reduce administrative costs (U.S. Government Accountability Office 2012).

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NOTES

1. While Section 203 of CHIPRA authorized ELE and permitted states to rely on findings from an Express Lane agency to conduct simplified eligibility determinations, some ELE-like efforts started prior this legislation. For example, in Maryland, the first outreach mailings on the basis of tax return information started in 2008, which is the event considered by state staff to be the start of ELE in that state. This issue is addressed in the sensitivity analysis.
2. Prior studies have used descriptive or qualitative methods to examine the experiences of a single state (e.g., Louisiana in Dorn, Hill, and Adams 2012) or the experiences of early adopting ELE states (e.g., reviews of ELE policies in Alabama, Iowa, Louisiana, and New Jersey in Families USA 2011).
3. At the time of this analysis, MSIS data were only available through 2009. There is even a longer lag with the MAX data.
4. Regardless, these two states would have been excluded from the analysis based on results from the pre-2009 trend models used to select comparison states.
5. An analysis of descriptive administrative data finds that children enrolling through ELE appear to be similar to other Medicaid and CHIP enrollees in most respects except that larger proportion of ELE enrollees are teenagers (Hoag et al. 2012).
6. Administrative verification of income allows states to move away from paper documentation of income to verification of income through electronic data matches with other data sources and/or contacts with third parties, such as employers, private and public wage databases, and other public programs (Stephens 2013). In contrast, ELE applies to additional eligibility findings besides than income, but it can only rely on other specified public programs in the state.
7. We also estimate a model restricted to separate CHIP programs only, but this model is limited by a smaller sample size of states adopting ELE policies that target CHIP and much smaller number of enrollees in each state. The ELE coefficient varied in magnitude across all of the model specifications and we did not find any evidence that that the ELE programs through CHIP had a statistically significant effect on separate CHIP enrollment. However, these results could be attributable to insufficient power as the sample size and potential ELE effect size are more limited in the separate CHIP models.

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Supporting Information

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

Appendix SA2: Changes in Medicaid/CHIP Policy from 2007 to 2011 among ELE and Non-ELE States.